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H.264 CODING ARTIFACTS AND THEIR RELATION TO PERCEIVED ANNOYANCE

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ABSTRACT

In this study we investigate coding artifacts in H.264 baseline profile. A psychophysical experiment was conducted that collected data about the subjectively perceived annoyance of short video sequences as well as the perceived strength of three coding artifacts. The data provided by 52 subjects is analyzed with respect to bitrate and intra period of the encoded sequences. A new data analysis method is presented which is based on a granular data representation and enables the detection of multidimensional functional dependencies in data sets. This method is employed to establish a model for the perceived annoyance as a function of artifact strength.

1. INTRODUCTION

H.264 is the latest video compression standard of the ITU Video Coding Experts Group. It has drawn a lot of attention lately as it outperforms existing standards considerably with respect to compression efficiency [2, 4]. In a video transmission chain several factors influence and impair the quality of the resulting imagery. One of these factors is the source coding algorithm itself. As a consequence of lossy coding a noticeable degradation of the video quality may be observed. It is thus important to have a video quality metric to optimally trade off compression ratio against quality. As digital video usually addresses a human observer it is of particular importance to develop video quality metrics that closely reflect the perceived quality. In many cases it is furthermore desirable that the employed metric does not utilize any information about the original video (no reference metric). Recent research efforts have therefore strived to develop metrics of a limited number of features of the impaired video [1]. A perceptual feature of an impairment in a video sequence is called an 'artifact' [1]. Our main objective is to develop a model that describes the perceived annoyance of a compression impaired video as a function of the perceived strength of the most dominant coding artifacts in H.264 baseline profile. For this purpose an experiment was carried out that measured the perceived strength of 'blurring', 'blocking' and 'flickering' artifacts, as well as the perceived overall annoyance caused by these impairments. Furthermore we study how these four quantities depend on two coding parameters: Bitrate and intra period (IP).

2. METHODOLOGY

2.1 Videos and Coding Parameters

The test sequences were produced using the four videos 'foreman', 'flower', 'bus' and 'football'. The H.264 reference software JM9.6 was used to encode these videos at sixteen different bitrate-IP combinations. Hence the whole test set comprised 64 sequences. In particular we used the four bitrates 100, 160, 230 and 300 $Kbps$ respectively, because the greatest variations in terms of artifact emergence were found in this interval. The format of the employed videos was CIF. The intra period (IP) was set to 10, 25, 40 and ∞ respectively. By '$IP = \infty$' we mean that only the first frame of the sequence was an I-frame and all following frames were P-frames. All relevant information regarding the videos employed are as follows:

- Format: CIF (288×352)
- Employed videos: Foreman, Flower, Bus, Football
- Frame rate: 25 fps
- Bitrates: 100, 160, 230, 300 $Kbps$
- IP: 10, 25, 40, ∞
- Duration of each sequence: 5 *sec.*

2.2 Description of the Experiment

A single stimulus experiment was conducted in two stages. During the first stage the *annoyance caused by all visible impairments in the entire sequence* was assessed. The strength of the single artifacts was then rated in the second stage. 'Strength' should also be understood in terms of '*How noticeable is an artifact with respect to the whole sequence*?'. We also offered a fourth artifact category labeled as 'Other' which was to be used in case the subject was not able to classify the detected impairment as proposed. Both stages were structured equally and split into three parts. During part one of each stage a reference level for the requested judgment was set which was defined by a reference sequence. The subjects were instructed to make all their judgments with respect to the reference level at any time. In part two the subjects were given five practice trials before data was recorded during the actual experiment in part three. An LCD-monitor with a resolution of 1080×1024 was used as a display. The subjects were seated in the distance of 60 cm in front of the display which was adjusted on eye level. The same viewing distance for all subjects was assured by the use of a chin-rest.

3. DATA ANALYSIS METHODS

The most relevant columns of our data table can be seen in Table 1. This is the basis for the analysis as presented in the following. For each subject s from the set of 52 subjects and each video sequence v from the set of 64 differently encoded sequences the subjective scores of subject s for video sequence v with respect to the *measurement functions Annoyance*, *Blurring*, *Flickering* and *Blocking* are recorded in a row of the data table with $N := 52 \times 64 = 3328$ rows. The N pairs (s, v) are coded by the elements k of an artificial key K, understood as the set $K := \{1, ..., N\}$. For each of the measurement functions the subjective scores are

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K	s	v	Annoyance(k)	Blurring(k)	Flickering(k)	Blocking(k)
1	1	1	80	19	20	14
2	1	2	71	22	1	13
⋮	⋮	⋮	⋮	⋮	⋮	⋮
64	1	64	23	33	4	17
65	2	1	60	5	1	22
⋮	⋮	⋮	⋮	⋮	⋮	⋮
N	52	64	0	0	0	0

Table 1: Data Table

elements of the set

$$M = \{m \in \mathbb{R} \mid 0 \leq m \leq 100\}. \tag{1}$$

3.1 Mean Observer Score

First we introduce the mean observer score for every video sequence v and task $Z \in \{Annoyance, Blurring, Flickering, Blocking\}$:

$$MOS_Z(v) = 52^{-1} \sum_{s=1}^{52} Z(s, v). \tag{2}$$

$Z(s, v)$ denotes the subjective score of subject s assigned to video v at task Z. In the case of the annoyance task the MOS is called mean annoyance value (MAV) and in the case of a strength task we refer to the MOS as mean strength value (MSV).

3.2 A Granularity based Approach for Analyzing Multidimensional Data

In this section a new data analysis method is described that enables the detection of multidimensional functional dependencies in data sets. The basic two dimensional procedure as well as the four dimensional generalization were first presented in [3].

3.2.1 Scaling of the Data

The measured data is scaled by a granularity mapping

$$Q_g\colon\ M \ \rightarrow \{1, \ldots, g\}, \tag{3}$$

where g is an integer number, greater or equal to one, that denotes the granularity chosen for the representation of the data. In particular this mapping is achieved by a uniform quantizer:

$$Q_g(m) = \begin{cases} \ulcorner(\frac{g \cdot m}{100})\urcorner, & \text{for } m \neq 0, \\ 1, & \text{for } m = 0. \end{cases} \tag{4}$$

The data may now be represented in any desired granularity prior to the analysis described next.

3.2.2 The Basic Two Dimensional Procedure

Let I and J be integers, interpreted as the number I of rows and the number J of columns of a contingency table. Let

$$X\colon K \rightarrow \{1, \ldots, I\} \text{ and } Y\colon K \rightarrow \{1, \ldots, J\}, \tag{5}$$

be two discrete functions interpreted as *granular measurement functions*. They map each key element k to a value $X(k) = i$ and $Y(k) = j$ respectively. The number

$$n_{ij} = |\{k \in K \mid X(k) = i,\ Y(k) = j\}|. \tag{6}$$

is called the absolute frequency in the cell (i, j) of a contingency table $C(i, j)$. The observed relative frequencies O_{ij} are then obtained by normalizing each entry of the contingency table by the number $N = |K|$ of key elements:

$$O_{ij} = \frac{n_{ij}}{N}. \tag{7}$$

From this table we process the the elements of the marginal distributions:

$$O_i = \sum_{j=1}^{J} O_{ij}, \text{ and } O_j = \sum_{i=1}^{I} O_{ij}. \tag{8}$$

As usual the two mappings X and Y are called statistically independent if $O_i \cdot O_j = O_{ij}$ for all cells (i, j). If X and Y are not statistically independent then there are cells such that the 'expected value'

$$E_{ij} = O_i \cdot O_j, \tag{9}$$

differs from the observed value O_{ij}. Therefore

$$D_{ij} = \begin{cases} (\frac{O_{ij} - E_{ij}}{E_{ij}}), & \text{for } (E_{ij} \neq 0) \text{ and} \\ & (O_{ij} \geq T \text{ or } E_{ij} \geq T), \\ 0, & \text{else,} \end{cases} \tag{10}$$

is computed, where T denotes a threshold. D_{ij} is understood as the relative deviation from statistical independency in cell (i, j). Finally, a second threshold P defines what percentage is considered to be significant:

$$S_{ij} = \begin{cases} D_{ij}, & \text{for } (D_{ij} \leq -P) \text{ or } (D_{ij} \geq P) \\ 0, & \text{else.} \end{cases} \tag{11}$$

A negative S_{ij} tells us that the observed rate in cell (i, j) is significantly smaller (with respect to the chosen threshold P) than the expected rate, whereas a positive S_{ij} indicates that the observed rate in cell (i, j) exceeds our expectation significantly.

3.2.3 Estimation

In case there is a dependency between X and Y, we get an idea of a partial meaning of this dependency by looking at those cells that show the *highest positive deviation from statistical independence*. For every row i, we select the set of those j for which S_{ij} is maximal with respect to all cells of the i-th row:

$$\mu(i) := \{j \mid S_{ij} > S_{lj},\ S_{ij} \neq 0,\ \forall\ l,\ l\ \in \{1, \ldots, J\}\}. \tag{12}$$

In order to obtain an estimate for the original *unscaled* quantity which had been represented in $Y_g(k)$, we first introduce an 'inverse' scaling operation Q'_g as:

$$Q'_g(x) = (x - 1) \cdot \frac{100}{g} \ + \ \frac{100}{2g}. \qquad \text{for } x = 1 \text{ to } g \tag{13}$$

A unique value $H(i)$ is then assigned to each i by averaging the inverse scaled elements of $\mu(i)$. This may be an estimate for an annoyance value with respect to the i-th artifact-strength combination for instance. Let $\Gamma_i := |\mu(i)|$ be the number of elements in $\mu(i)$. Since the mapping Q'_J is injective, we also get $\Gamma_i = |Q'_J(\mu(i))|$ and hence

$$H(i) = \Gamma_i^{-1} \cdot \sum_{x\ \in\ \mu(i)} Q'_J(x) \quad (\forall\ i \mid \mu(i) \neq \emptyset), \tag{14}$$

is the average of the inverse scaled values of $\mu(i)$.

3.2.4 Four Dimensional Generalization

As the inspection of a four dimensional relation is of particular interest in this study, the contingency table $C(i,j)$ is extended to four dimensions. It should be noted that we are not constraint to four dimensions. At first we define three additional granular measurement functions:

$$X1\colon\ K \quad\rightarrow\quad \{1,\dots,I1\} \tag{15}$$
$$X2\colon\ K \quad\rightarrow\quad \{1,\dots,I2\} \tag{16}$$
$$X3\colon\ K \quad\rightarrow\quad \{1,\dots,I3\}. \tag{17}$$

These will be used to represent the strengths of the three artifacts in their respective granularities $I1$, $I2$ and $I3$. The tuple

$$X(k) := (X1(k),\ X2(k),\ X3(k)) \tag{18}$$

is now considered as one measurement. Thus the product of X and Y, hence $X1 \times X2 \times X3 \times Y$, is used as our representation of the four measurements. This yields the four dimensional contingency table, where every cell $C(i,j) = (i1,i2,i3,j)$ is assigned the absolute number of elements in the respective pre-image of $X1 \times X2 \times X3 \times Y$:

$$\begin{aligned} n_{i1i2i3j} \quad &= \quad |\{k \in K \mid X1(k) = i1,\ X2(k) = i2, \\ &\quad\ X3(k) = i3,\ Y(k) = j\}|. \end{aligned} \tag{19}$$

The basic two dimensional procedure as described previously can now be applied to X and Y without any further modifications.

4. RESULTS

4.1 Mean Annoyance and Mean Strength

The MAVs and MSVs in the 'foreman' video mainly show a monotonically decreasing course in both dimensions, except for the average flickering strength (see Figure 1(a)). Especially at $IP = 40$ the average strength of the flickering increases with bitrate and furthermore dominates the composition of artifacts. Blurring dominates over blocking for all sixteen bitrate - intra period combinations.

The MSVs in the 'flower' video show that flickering is clearly perceived as the strongest artifact as can be seen from Figure 1(b). All three artifacts are assigned rather low MSVs at $IP = \infty$. Again the parameter combination 300 $Kbps$ and $IP = 40$ emerges from the other parameter combinations, and the slight trend propagates into the MAVs.

Studying the MSVs for the 'bus' sequence in Figure 1(c) we find that the blocking artifact is perceived as the most dominant phenomenon in this video. Again we observe an increasing trend in the MSVs towards the highest bitrate with respect to the flickering. The impact of the intra period within this video is rather small when compared to the impact of the bitrate.

The data for the 'football' video exhibits that blocking and blurring are assigned approximately the same MSVs and moreover they dominate over flickering. Figure 1(d) shows that the MSVs of the two effects decrease towards higher data rates at a generally high level. The MAVs and MSVs further on tell us that the intra period has almost no impact on the obtained averages, which is in contrast to the bitrate. It seems that 300 $Kbps$ is not sufficient to encode this sequence such that the majority of observers is not annoyed by the coding artifacts.

Hence the obtained data shows that the video content has a great influence on the emergence of artifacts. For the same coding parameters completely different results are obtained. Roughly speaking we can say that the results for the different sequences share one trait: The mean annoyance values as well as the mean strength values decrease with increased bitrate and increased intra period. The 'football' video has the highest MAVs when compared to the other sequences. The 'foreman' video is found to exhibit the least annoying artifacts. The proposed classification of artifacts found broad acceptance among the participants since the category 'Other' was selected only three times.

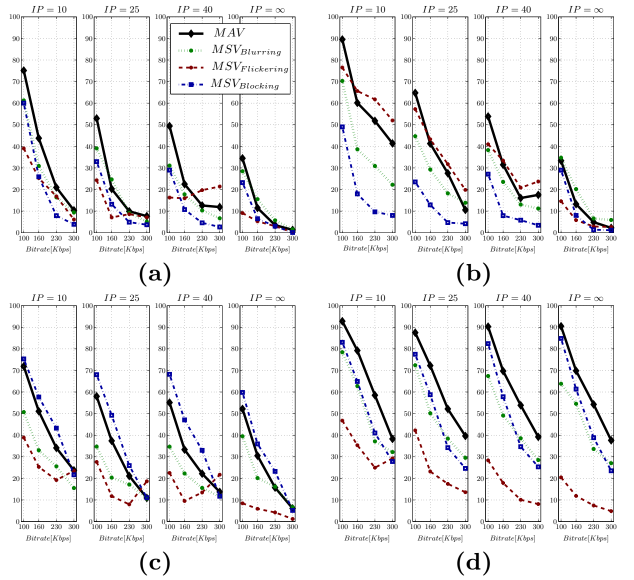


Figure 1: **MAVs and MSVs** for the four videos: (a): Foreman, (b): Flower, (c): Bus and (d): Football.

4.2 Granularity Based Analysis

In this section the results from the granularity based analysis as described in Section 3.2 are presented and discussed. The data is analyzed on a global level, without distinguishing video content or any other attributes. We analyze the data on different levels of granularity and use algebraic models as brief descriptions of the obtained results. All curve fitting is done using the 'Nelder Mead Simplex Algorithm'.

To gain a better understanding how the strength of an artifact relates to the perceived annoyance, we first analyze the data by looking at the marginal relations between annoyance and each artifact strength. Then the second dimension is unfolded, which gives insights to how the perceived annoyance relates to both blurring and blocking strengths. Finally the whole four dimensional relation between annoyance and the strength of the three artifacts is investigated in different granularities. The following denotations will be used throughout this section:

$$X1_{I1}(k) \quad := \quad Q_{I1}(Blurring(k)), \tag{20}$$
$$X2_{I2}(k) \quad := \quad Q_{I2}(Blocking(k)), \tag{21}$$
$$X3_{I3}(k) \quad := \quad Q_{I3}(Flickering(k)), \tag{22}$$
$$Y_J(k) \quad := \quad Q_J(Annoyance(k)). \tag{23}$$

4.2.1 Marginal Relations between Annoyance and Artifact Strengths

The marginal relations between annoyance and the strength of a single artifact are investigated by setting the granularities, used to represent the other two artifacts, to one. When $I1 = I3 = 1$ is chosen for instance, the relation between annoyance and blocking strength is analyzed. The respective 2-tuples $(Q'_{I2}(i2),\ H_J(i))$ describe the relation of interest with respect to the chosen granularities and thresholds. The granularity J and the resolution for the respective artifact strength are tied and then varied from 6 to 11. $P = 0.3$ and $T = 4/N$ are used as thresholds. This analysis is performed for all three marginal relations. The results show that annoyance relates to each single artifact in a logistic manner. Therefore the logistic function:

$$y(x) = \frac{100}{1 - e^{-(x - x_{mid})G}}. \tag{24}$$

is fitted to the resulting 2-tuples. The root mean squared errors ($RMSE$s) as well as all resulting parameters of the fits are tabulated in Tables 3, 4 and 5. The best fits are obtained for the mapping between annoyance and blurring. The annoyance-blocking relation yields consistent parameters across different granularities too, and the obtained parameters are furthermore similar to those for annoyance and blurring, though the errors are a little higher. The mapping between annoyance and flickering results in the highest errors, but the logistic trend can still be observed. Hence we note three marginal logistic mappings whereas the blurring-annoyance mapping gives us the highest confidence in the detected relation. Figure 2(a) shows the best fit from this analysis.

4.2.2 Annoyance as a Function of Blurring and Blocking

The next step of the granularity analysis is to explore how different combinations of blocking and blurring strength contribute to the perceived annoyance. For $I3 = 1$, $P = 0.5$ and $T = 4/N$ we obtain results that correspond to our intuitive idea of the nature of this relation. Based on these observations and on the knowledge about logistic marginal relations between annoyance and artifact strength, the following two-dimensional model is formulated:

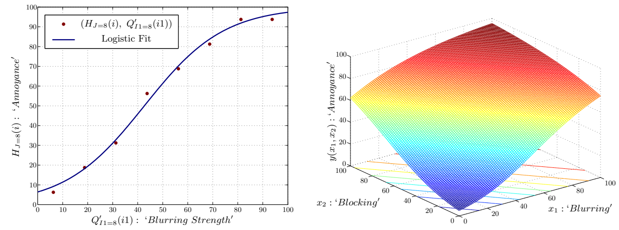
$$y(x_1, x_2) = \frac{100}{[1 - e^{-(c_1(x_1 - x_{1mid}) + c_2 x_2)G_1}]} \cdot \frac{1}{[1 - e^{-(c_1 x_1 + c_2(x_2 - x_{2mid}))G_2}]}. \tag{25}$$

Hence the relation is modelled by the product of two logistic mappings whereas the weights c_1 and c_2 for the artifact strength are introduced to quantify to what extent an artifact contributes to the perceived annoyance. The sums in the exponents are based on the assumption that the annoyance should remain constant as long as the weighted sum of artifact strength is constant. For the analysis the granularities $I1$ and $I2$ are fixed to $I1 = I2 = 5$ and the granularity J for the annoyance is varied. The model in Eq. (25) is thus fitted to the 3-tuples $(Q'_{I1=5}(i1),\ Q'_{I2=5}(i2),\ H_J(i))$. The resulting parameters of these fits are tabulated in Table 6. Figure 2(b) shows the resulting model for the best fit ($I = 6$). The obtained weights c_1 and c_2 for blurring and blocking do not show distinct differences. Hence blocking and blurring seem to contribute to the annoyance to approximately the same extent.

4.2.3 Annoyance as a Function of Blurring, Blocking and Flickering

The model in Eq. (25) describes the perceived annoyance as a monotonically increasing function. This assumption should hold when flickering is considered as the third artifact dimension. For symmetry reasons and because it is the most intuitive next modelling step, the model in Eq. (25) is extended as follows:

$$y(x_1, x_2, x_3) = \frac{100}{[1 - e^{-(c_1(x_1 - x_{1mid}) + c_2 x_2 + c_3 x_3)G_1}]} \cdot \frac{1}{[1 - e^{-(c_1 x_1 + c_2(x_2 - x_{2mid}) + c_3 x_3)G_2}]} \cdot \frac{1}{[1 - e^{-(c_1 x_1 + c_2 x_2 + c_3(x_3 - x_{3mid}))G_3}]}. \tag{26}$$



(a) **(b)**

Figure 2: (a): **Annoyance** as a function of **blurring**: Their relation can be described by a logistic mapping. (b): **Annoyance** as a function of **blurring and blocking.**

Hence we assume a logistic dependency for the new dimension as well, though the marginal relation between annoyance and flickering is the one the least pronounced in our data. For the analysis we proceed as in the previous section and fix all three artifact resolutions to $I1 = I2 = I3 = 5$, whereas the granularity for the annoyance is varied. Then the model in Eq. (26) is fitted to the 4-tuples $(Q'_5(i1),\ Q'_5(i2),\ Q'_5(i3),\ H_J(i))$. Table 7 shows the results of these fits. We recognize almost the same goodness of fit for all granularities, whereas the $RMSE$s are relatively high when compared to the marginal annoyance-blurring fit for instance. Except for $J = 6$ the blocking artifact has the highest weight (c_2), which however does not conform to the values in Table 6.

The $RMSE$ is a measure for the goodness of the fit, but it does not give us further evidence about the validity of the model with respect to our data set. To test whether the model in Eq. (26) reflects the average responses, it is used to predict the MAVs from the MSVs. It should be noted that neither the MAVs nor the MSVs have been used during the modelling process. To quantify the goodness of these predictions we use the square of the correlation coefficient R between the result of the prediction and the MAVs their selves as well as the $RMSE$ between both. In Table 2 the R^2 values and $RMSE$s for all considered parameter settings are tabulated.

J	6	7	8	9	10	11
RMSE	5.35	7.54	7.07	6.25	6.79	7.21
R^2	0.9560	0.9217	0.9319	0.9425	0.9360	0.9358

Table 2: Goodness of MAV prediction.

Thus the model in Eq. (26) can be considered to be a good estimator for the mean annoyance values for all obtained parameter sets.

The result indicates that the model is indeed reasonable for our data set and that the granularity analysis yields useful results. Moreover the confidence in all previous results obtained through the granularity based approach is increased considerably as they led to the formulation of the model. Though $J = 6$ did not yield the best fit, it turns out that the parameters for this case result in the best predictor. The respective comparison of the predicted MAVs and the MAVs their selves is therefore presented in Figure 3.

5. CONCLUDING REMARKS

Four different videos were used in a psychophysical experiment. An artifact classification has been proposed. It could be confirmed experimentally that blurring, blocking, and flickering artifacts can be considered to be the most

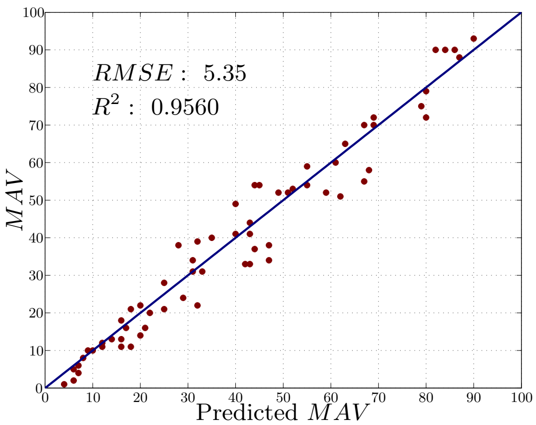


Figure 3: Comparison of predicted and actual MAVs: The model provides a good estimator.

relevant coding impairments in the baseline profile. It has been shown that the content of a video has a major impact on the emergence of coding artifacts. Nevertheless global content-independent dependencies were found by means of a new data analysis method. The perceived annoyance of an H.264 encoded video sequence was related to the strength of three coding artifacts using a model based on logistic mappings. It has been shown that the model can be used to predict the mean annoyance values from the mean strength values which emphasizes that the granularity based approach yields reasonable results. The model can potentially be used to estimate the subjectively perceived annoyance which should be subject to minimization during encoding and/or postprocessing. Future work should therefore focus on the development of artifact metrics for all three investigated artifacts.

(I, J1)	(6, 6)	(7, 7)	(8, 8)	(9, 9)	(10, 10)	(11, 11)
RMSE	7.14	4.50	2.48	13.85	8.03	6.45
x_{mid}	43.14	48.23	42.62	35.16	38.60	36.86
G	0.0557	0.0557	0.0629	0.0686	0.0564	0.0620

Table 3: Fitting parameters for the **blurring-annoyance** relation.

(I, J2)	(6, 6)	(7, 7)	(8, 8)	(9, 9)	(10, 10)	(11, 11)
RMSE	7.14	5.93	11.16	12.86	5.43	10.16
x_{mid}	43.14	42.93	42.05	44.16	38.27	42.65
G	0.0557	0.0575	0.0509	0.0441	0.0668	0.0565

Table 4: Fitting parameters for the **blocking-annoyance** relation.

(I, J3)	(6, 6)	(7, 7)	(8, 8)	(9, 9)	(10, 10)	(11, 11)
RMSE	10.57	10.87	13.08	13.21	12.77	16.30
x_{mid}	33.70	44.89	37.17	37.33	32.82	37.02
G	0.0991	0.0656	0.1392	0.0674	0.0443	0.0503

Table 5: Fitting parameters for the **flickering-annoyance** relation.

I	6	7	8	9	10	11
RMSE	8.97	10.43	10.76	10.58	10.14	9.87
c_1	1.14	0.97	1.01	1.06	1.04	1.04
c_2	0.91	1.01	0.91	0.90	0.96	0.89
x_{1mid}	40.30	29.06	12.75	21.71	33.62	34.68
x_{2mid}	44.08	53.28	52.57	48.92	47.58	47.33
G_1	0.0189	0.0190	0.0166	0.0178	0.0185	0.0118
G_2	0.0398	0.0578	0.0586	0.0475	0.0448	0.0454

Table 6: Fitting parameters for the model in Eq. (25).

I	6	7	8	9	10	11
RMSE	13.95	13.76	14.54	13.21	12.68	12.51
c_1	1.14	0.74	0.82	0.76	0.82	1.10
c_2	1.14	1.41	1.29	1.12	1.24	1.32
c_3	0.92	0.67	0.73	0.86	0.72	0.62
x_{1mid}	75.48	64.22	70.41	73.58	75.74	80.27
x_{2mid}	14.85	27.56	34.29	21.75	26.54	25.40
x_{3mid}	17.25	26.07	28.65	20.43	24.30	20.46
G_1	0.0149	0.0137	0.0142	0.0166	0.0171	0.0177
G_2	0.0275	0.0315	0.0352	0.0292	0.0311	0.0306
G_2	0.0388	0.0458	0.0486	0.0410	0.0442	0.0409

Table 7: Fitting parameters for the model in Eq. (26).

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